SEQUENTIAL ORDERING OF ROUTES FOR TRUCKS FOR EFFICIENT GARBAGE COLLECTION: CASE STUDY OF SEKONDI –TAKORADI METROPOLITAN ASSEMBLY (STMA).

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ABSTRACT
This research paper presents a case study of a Vehicle Routing Problem (VRP). The objective is to minimize the total lengths taken by trucks of the Waste Management Department of Sekondi-Takoradi Metropolitan Assembly in transporting solid waste from the Metropolis to the Dump Site. The problem was formulated as an Integer Programming Model and the Ant Colony Meta-heuristic for the Travelling Salesman Problem was used to obtain the optimal solution. Data on distances between potential garbage picking points were obtained, and the Cartesian coordinates of the various garbage collection points were collected and used as a distance matrix table for each zone. The optimal solutions were obtained with the help of a Matlab implementation codes. The results revealed an outstanding performance of the Ant Colony Optimization Algorithm in terms of efficiency. The study revealed a reduction of the total cost by GH$56000.35 which represents 35% of the total cost.

Key words:
Garbage, Solid Waste Management, Ant Colony, Vehicle Routing Problem, Metaheuristics.

INTRODUCTION

Solid waste refers to wastes from households, municipal services and construction debris. This also includes non-hazardous, non-liquid wastes from institutions and industries. According to the World Bank (2001), its generation is greatly affected by a country's development. Generally, the more economically prosperous a country is, the more waste is generated per capita. Solid Waste Management (SWM), on the other hand, pertains to the control of the generation, storage, collection, transfer and transport, processing and disposal of solid waste in a fashion that is in accordance to societal and economic needs while at the same time compliant to environmental standards and principles. Solid waste is a telltale sign of how citizens' lifestyles change as a result of economic development. Furthermore, the distribution of waste generation in different regions of a country is indicative of its degree of urbanization. In cities, where standard of living is higher, there is usually a higher waste output compared to rural areas. This is reflective of the case of a developing country like Ghana where its Western Regional capital (Sekondi-Takoradi) generates almost a quarter of the country's total waste generation (STMA, 2010).

Transportation of solid waste product from the cities in Ghana to the destinations for proper disposal has become a unique aim of most metropolitan assemblies in order to make the cities clean from dirt and prevent the outbreak of some diseases and also make the environment smell good. Recent events in major urban centres in Africa have shown that the problem of waste management has become a monster that has aborted most efforts made by city authorities, state and federal governments, and professionals alike. A visit to any African city today will reveal aspects of the waste-management problem such as heaps of uncontrolled garbage, roadsides littered with garbage, disposal sites constituting a health hazard to residential areas, and inappropriately disposed solid wastes.

In Sekondi-Takoradi Metropolitan Assembly (STMA) has trucks to run to and from various collection points where garbage are gathered to the destination for disposal. It is hard to believe that most of the garbage containers may get full but the trucks may not be available for collection. This resulted into inefficient ordering of trucks to routes. The task of finding an efficient route is an important logistic problem (Bell and McMullen, 2004). When a metropolis is able to reduce the length of its delivery route then it would be able to provide a better service to the community and the nation at large. A typical truck routing problem involves determining the routes for several trucks from a given garbage points and returning to the disposal destination without exceeding its capacity.

RELATED WORKS

Ghiduk (2010) presented ant colony optimization based approach for generating a set of optimal paths to cover all definition –use associations (du-pairs) in the program under test. The objective was to use ant colony optimization to generate suit of test-data for satisfying the generated set paths. The authors introduced a case study to illustrate their approach and the algorithm proved to be very efficient. Dorigo and Gambardella (1997) introduced ant colony systems (ACS) to the TSP. In order to understand the operation of the ACS, experiments were conducted and the results showed that ACS outperforms other nature-inspired algorithms such as simulated annulling and evolutionary computations. The authors concluded by comparing ACS-3-opt, a version of ACS augmented with a local search procedure to some of the best performing algorithms for symmetric and asymmetric TSP's. Amponsah and Salhi (2004) used the Variable Neighbourhood Search Method to solve the solid waste problem in the Kumasi Metropolitan Area.

ASSUMPTIONS OF THE PROPOSED MODEL

The problem is how to transport solid waste from the city to the dump site for disposal. Residences are geographically dispersed around the depot and each truck is unique in terms of capacity. The following assumptions were made:

(i) Service is available to only customers whose residence is not within a walking distance to the dump site.
(ii) All customers to be serviced must walk to an allowed garbage picking point to dump the waste.
(iii) A truck must visit a given picking point only once.
(iv) Capacities of trucks must not be exceeded.

NOTATIONS

The notations were used in the study

K_t = Capacity of truck t

T = Number of trucks

C_{ij} = Cost of traversing arc from i to j

S = Set of all potential picking points

G_{gi} = Binary variable that shows if a customer g can walk to picking point i or not

A = Set of all arcs between picking points.

O = Set representing the dump site or the depot

Decision Variables

$N_{(t)\ ij}$ = Number of times truck t traverses arcs from i to j

$$V_{(t)_i} = \begin{cases} 1, \text{if truck } t \text{ visit stop } i \\ 0, \text{otherwise} \end{cases}$$

$$P_{(t)_{ig}} = \begin{cases} 1, \text{if truck } t \text{ picks up garbage of customer } g \text{ at picking point } i \\ 0, \text{otherwise} \end{cases}$$

THE PROPOSED MODEL

$$\text{Min } f = \sum_{(i;j)\in s} C_{ij} \sum_{t=1}^{4} N_{(t)\ ij} \qquad (1)$$

$$s.t \quad \sum_{t=1}^{4} V_{(t)_o} \le 4\,, \quad t = 1,2,3,4 \qquad (2)$$

$$\sum_{j\in s} N_{(t)\ ij} = \sum_{j\in s} N_{(t)\ ij} = V_{(t)_i}\ , \ \forall\, i \in S, \quad t = 1,2,3,4 \qquad (3)$$

$$\sum_{i\in G}\sum_{j\notin G} N_{(t)\ ji} \ge V_{(t)_h}, \quad \forall G \le S\backslash\{0\}, h \in g, \ t = 1, \dots, 4 \qquad (4)$$

$$\sum_{t=1}^{4} V_{(t)_i} \le 1, \ \forall i \in S\backslash\{0\} \qquad (5)$$

$$\sum_{t=1}^{4} P_{(t)_{ig}} \le G_{gi}\,, \forall g \in G, i \in S \qquad (6)$$

$$\sum_{i\in S}\sum_{g\in G} P_{(t)_{ig}} \le K_t, \ t = 1,2,3,4 \qquad (7)$$

$$P_{(t)_{ig}} \le V_{(t)_i}, \forall i \in S, g \in G, t = 1,2,3,4 \qquad (8)$$

$$\sum_{i\in s}\sum_{t=1}^{4} P_{(t)_{ig}} = 1\,, \ \forall g \in G \qquad (9)$$

$$V_{(t)_i} \in \{0, 1\}\,, \forall i \in S\,, \ t = 1,2,3,4 \qquad (10)$$

$N_{(t)\ ij} \in \{0,1\}, \forall i,j \in S \backslash i \neq j$ (11)

$P_{(t)_{ig}} \in \{0,1\}, \forall i,j \in S \backslash i \neq j$ (12)

The objective function (1) minimizes the total route length covered by all trucks. Constraint (2) ensures that all trucks start from the depot (i.e. O). Constraint (3) ensures that if truck t visits picking point i then one arc is traversed by t entering and exiting i. Constrain (4) prevents the formation of sub-tours. This means that each cut defined by a customer set G is crossed by a number of arcs not less than the minimum number of trucks $n(T)$ required to serve set G. Constraint (5) ensures that a truck visits a particular picking point not more than one. Constraint (6) stipulates that every customer walks to his designated picking point only. Constraint (7) guarantees that respective capacities of trucks are not exceeded. Constraint (8) ensures that garbage of costumer g designated to picking point i is picked up by truck t provided t visits stop i. Constraint (9) ensures that garbage of all costumers are picked up only once. Finally, (10), (11) and (12) represent the binary internality constraints on all decision variables.

ANT COLONY OPTIMIZATION

Ant Colony Optimization is one of the newest metaheuristic for the application to Combinatorial Optimization problems. The basic ideas of ACO were introduced in Dorigo (1992) and successively extended in Dorigo et al. (1999, 1996). St¨utzle and Dorigo (2002), Dorigo and St¨utzle (2002). In this section we present the description of ACO given in Dorigo and Di Caro (1999). ACO was inspired by the foraging behaviour of real ants. This behaviour—as described by Deneubourg et al., (1990)—enables ants to find shortest paths between food sources and their nest. Initially, ants explore the area surrounding their nest in a random manner. As soon as an ant finds a source of food, it evaluates quantity and quality of the food and carries some of this food to the nest. During the return trip, the ant deposits a pheromone trail on the ground. The quantity of pheromone deposited, which may depend on the quantity and quality of the food, will guide other ants to the food source. The indirect communication between the ants via the pheromone trails allows them to find the shortest path between their nest and food sources. This functionality of real ant colonies is exploited in artificial ant colonies in order to solve CO problems. In ACO algorithms the pheromone trails are simulated via a parameterized probabilistic model that is called the pheromone model. The pheromone model consists of a set of model parameters whose values are called the pheromone values. The basic ingredient of ACO algorithm is a constructive heuristic that is used for probabilistically constructing solutions using the pheromone values.

In general, the ACO approach attempts to solve a CO problem by iterating the following two steps:

(i) Solutions are constructed using a pheromone model, that is, a parameterized probability distribution over the solution space.

(ii) The solutions that were constructed in earlier iterations are used to modify the pheromone values in a way that is deemed to bias the search toward high quality solutions.

In the following we explain these three algorithm components in more detail Ant Based Solution Construction: As mentioned above, the basic ingredient of ACO algorithm is a constructive heuristic for probabilistically constructing solutions. A constructive heuristic assembles solutions as sequences of solution components taken from a finite set of solution components $C = \{c_1 \cdot \cdot \cdot, c_n\}$. A solution construction starts with an empty partial solution $s^p = <>$. Then, at each construction step the current partial solution s^p is extended by adding a feasible solution component from the set $N(s^p) \subseteq C \backslash S^P$.

The process of constructing solutions can be regarded as a walk (or a path) on the so-called construction graph GC = (C, L) whose vertices are the solution components C and the set L are the connections. The allowed walks on GC are hereby implicitly defined by the solution construction mechanism that defines the set $N(s^p)$ with respect to a partial solution S^P. The choice of a solution component from $N(s^p)$ is at each construction step done probabilistically with respect to the pheromone model, which consists of pheromone trail parameters T_i that are associated to components $C_i \in C$. The set of all pheromone trail parameters is denoted by T. The values of these parameters—the pheromone values—are denoted by τi. In most ACO algorithms

the probabilities for choosing the next solution component also called the transition probabilities are defined as follows:

$$P(C_i / S^P) = \frac{T_i^{\alpha}.n(C_i)^{\beta}}{\sum_{C_j \in N(S^P)} T_j^{\alpha}.n(C_j)^{\beta}}, \forall C_i \in N(S^P) \quad (13)$$

where n is a weighting function, which is a function that, sometimes depending on the current partial solution, assigns at each construction step a heuristic value $n(C_i)$ to each feasible solution component $C_i \in N(S^p)$. The values that are given by the weighting function are commonly called the heuristic information. Furthermore, α and β are positive parameters whose values determine the relation between pheromone information and heuristic information.

Pheromone Update

In ACO algorithms we can find different types of pheromone updates. First, we outline a pheromone update that is used by basically every ACO algorithm.

This pheromone update consists of two parts. First, a pheromone evaporation, which uniformly decreases all the pheromone values, is performed. From a practical point of view, pheromone evaporation is needed to avoid a too rapid convergence of the algorithm toward a sub-optimal region. It implements a useful form of forgetting, favouring the exploration of new areas in the search space. Then, one or more solutions from the current or from earlier iterations are used to increase the values of pheromone trail parameters on solution components that are part of these solutions. As a prominent example, we outline in the following the pheromone update rule that was used in Ant System (AS) Dorigo (1992), which was the first ACO algorithm proposed. This update rule is defined by

$$T_i = (1 - P).T_i + P.\sum_{\{S \in G_{iter} | C_i \in S\}} F(S) \qquad (14)$$

DATA COLLECTION AND ANALYSIS

The data involves length of distances between various picking points for each zone. The distances between picking points were measured and a grid map was used to find the cartesian coordinates which gave rise to the distance matrix as shown in the Tables 1.1. The distances were recorded with the aid of a car that reads distances digitally.

Table 1.1 Distance Matrix for Zone I, II, III and IV

S/NO	ZONE I		ZONE II		ZONE III		ZONE IV	
	X	Y	X	Y	X	Y	X	Y
1	625	90	618	96	626	75	621	89
2	624	92	621	95	635	78	621	88
3	622	89	622	96	622	75	622	88
4	625	88	617	96	624	79	619	90
5	626	88	620	91	625	82	622	90
6	627	85	620	93	625	81	623	89
7	626	86	622	93	626	79	623	91
8	626	87	621	91	627	78	617	87
9			623	94	627	82	616	88
10			625	97			614	89
11			623	96				

Source: Field Survey Dec. 2011.

Table 1.1 shows the Cartesian coordinates of the various garbage picking points in zone I, II, III and IV. The original total route length for zones I, II, III and IV for the collection of garbage are 30.22km, 38.18km, 46.15km and 38.23km respectively.

ANT COLONY OUTPUT FOR THE TRUCK ASSIGNED TO ZONE I

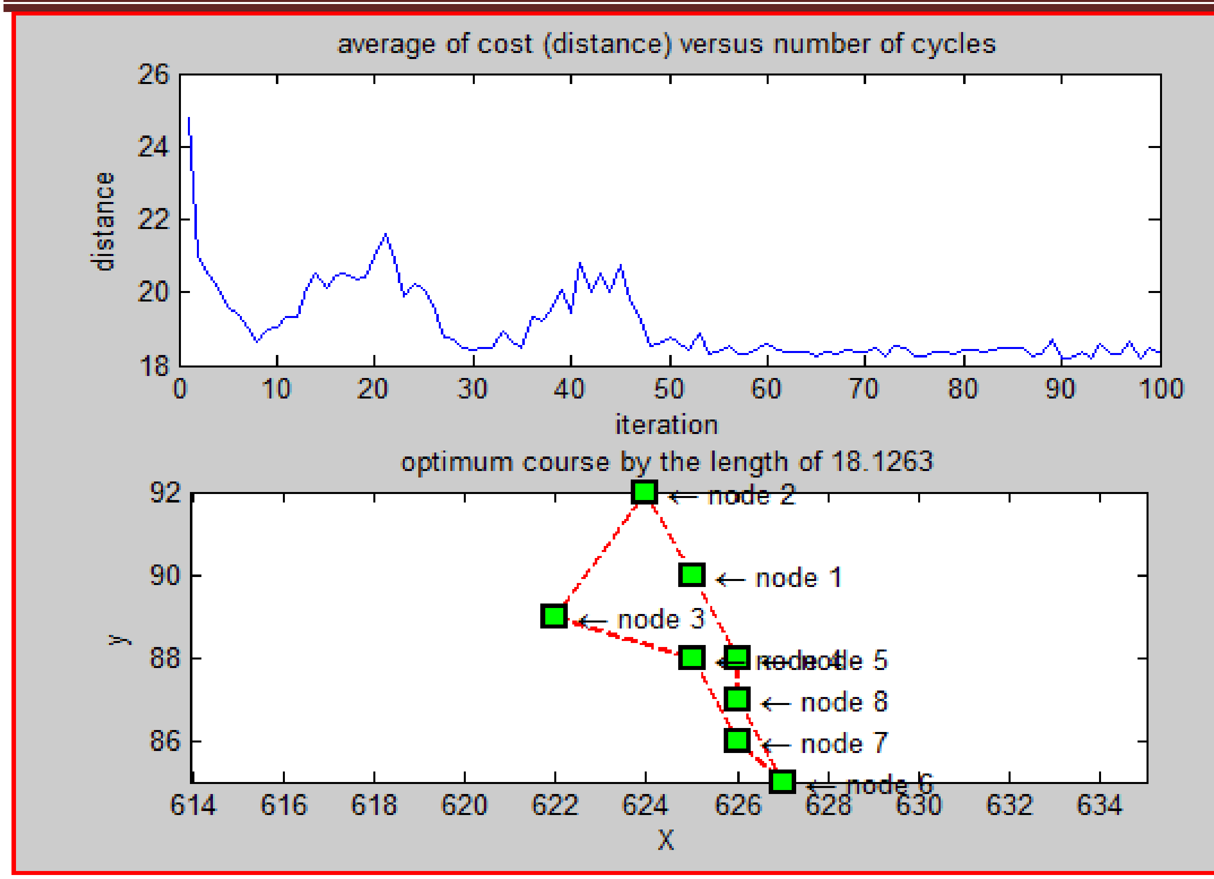

Figure 1.1: Ant colony result for 200 ants.

Figure 1.1 depicts that for 200 ants the best ant will cover an optimum course by the length of about 18.126km, which is better than the distance covered by the truck of zone I. This means that the optimal route length displaced by the truck of zone I using ant colony is 18.126km.

ANT COLONY OUTPUT FOR THE TRUCK ASSIGNED TO ZONE II

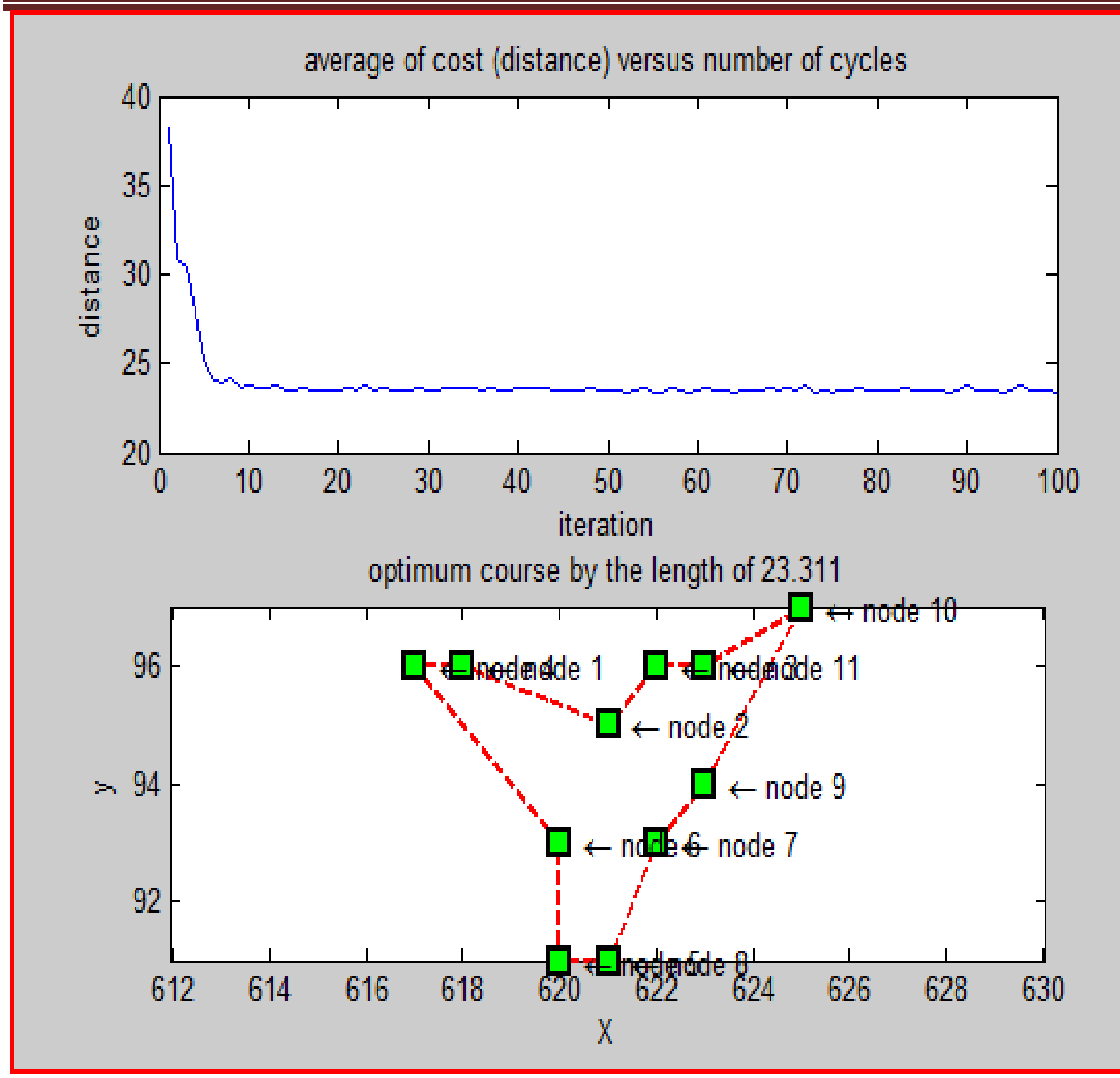

Figure 1.2: Ant colony result for 200 ants.

Figure 1.2 depicts that for 200 ants, the optimum length completed by the best out of 200 ants is approximately 23.311km. This shows a reduction of 39.5% of the original route length. The optimum course for truck of zone II using ant colony is approximately by the length of 23.311km.

ANT COLONY OUTPUT FOR THE TRUCK ASSIGNED TO ZONE III

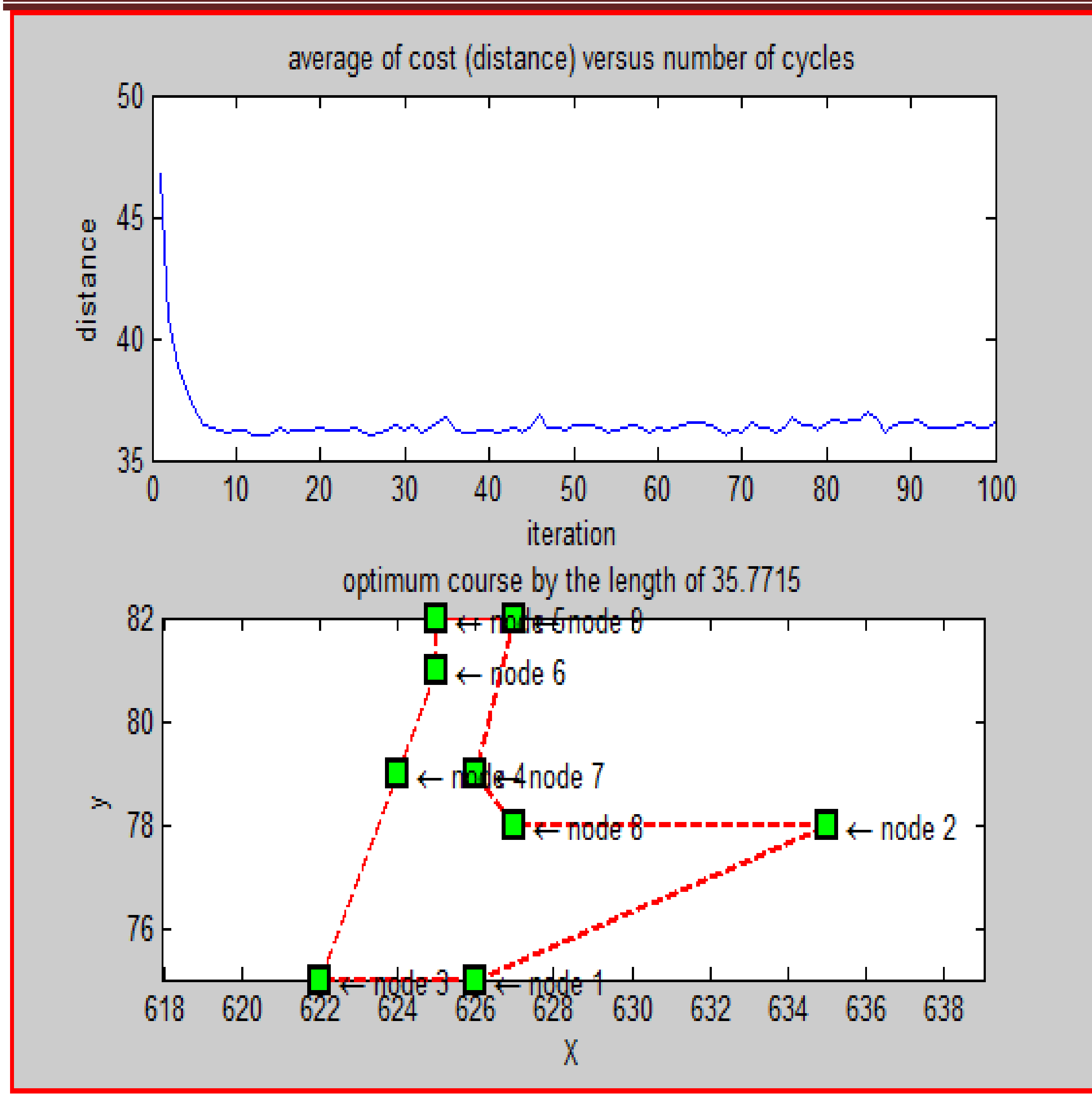

Figure 1.3: Ant colony result for 200 ants.

Figure 1.3 depicts that for 200 ants, the optimum length completed by the best out of 200 ants is approximately 35.772km. This shows a reduction of 21.7% of the original route length. The optimum course for truck of zone III using ant colony is approximately by the length of 35.772km.

ANT COLONY OUTPUT FOR THE TRUCK ASSIGNED TO ZONE IV

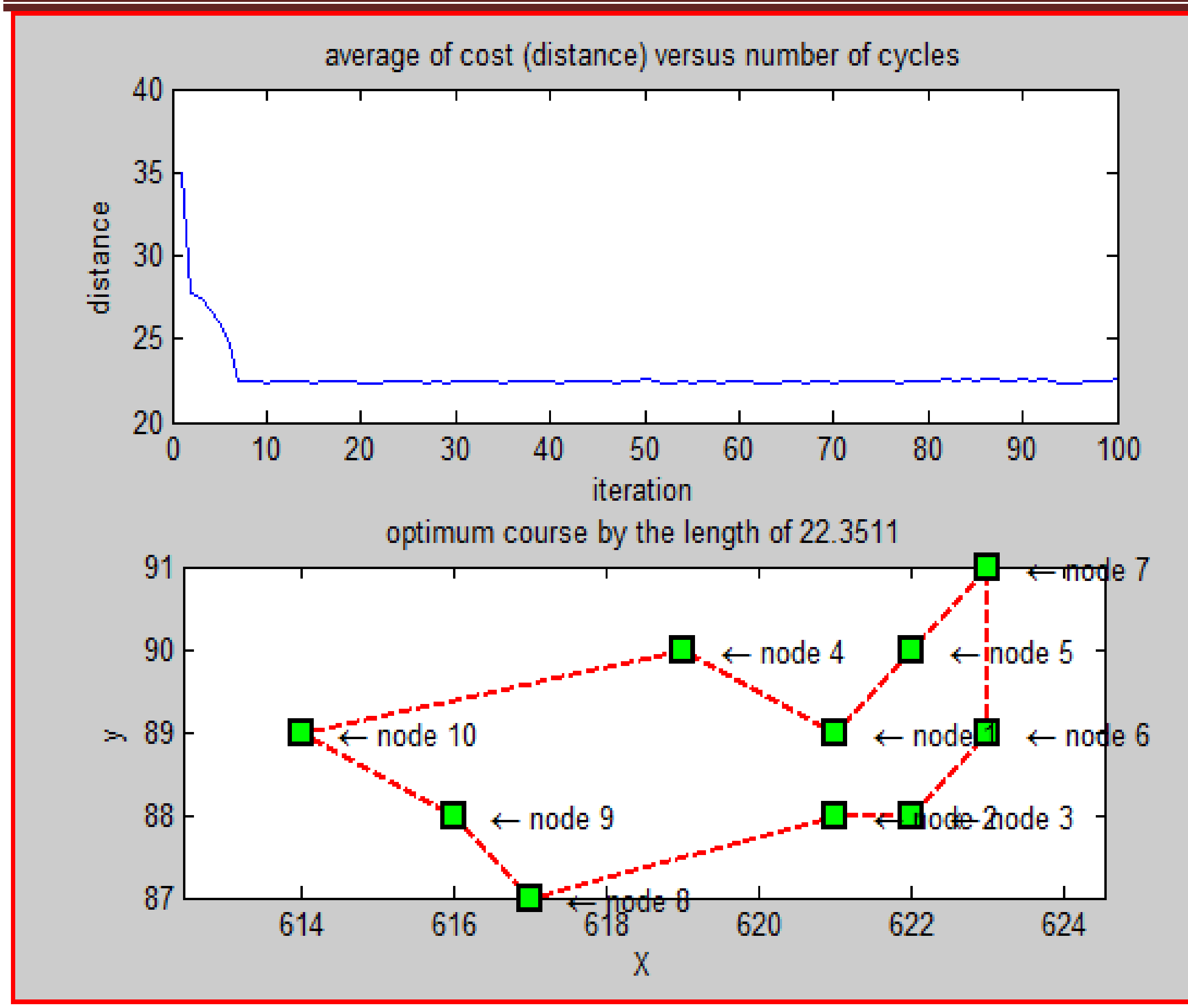

Figure 1.4: Ant colony result for 200 ants.

Figure 1.4 shows that for 200 ants, the optimum length completed by the best out of 200 ants is approximately 22.351km. This shows a reduction of 42.1% of the original route length. The optimum course for truck of zone II using ant colony is approximately by the length of 22.351km.

CONCLUSIONS

The ant colony optimization algorithm has shown that it is one of the most powerful tools for solving hard and complex combinatorial optimization problems like the VRP. Comparing the results of the ant colony to the existing transportation system at STMAWMD, the existing system is inefficient. The results show the possibility of the ant colony optimization heuristic to converge the solution to optimality. The following conclusions can be made based on the results.

(i) Optimal route length for trucks of zone I, II, III and IV are respectively 18.126km, 23.311km, 35.772km and 22.351km approximately.

(ii) Cost of services rendered by trucks of zone I, II, III and IV are reduced by 40%, 39.5%, 21.7% and 42.1% , respectively.

(iii) In general, the total cost of transporting the waste is reduced by approximately 35% which means the cost is reduced to GH$104000.65 instead of spending GH$160001.00 per month.

(iv) The number of potential garbage picking points that will be selected for trucks of zone I, II, III and IV are 8, 11, 9 and 10 respectively.

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